

Supplementary information

Unbiased estimation of the OLS covariance matrix when the errors are clustered

Empirical Economics

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Appendix A: Derivation of the unbiased variance estimators

Equicorrelated errors

In this section we consider the case where the errors are equicorrelated within clusters, so

$$\boldsymbol{\Sigma} = \sigma^2 \mathbf{I}_n + \tau^2 \mathbf{B}\mathbf{B}',$$

hence the design matrix for this case is

$$\mathbf{D} = (\text{vec } \mathbf{I}_n, \text{vec } \mathbf{B}\mathbf{B}').$$

Let

$$\begin{aligned} s &\equiv \text{tr}(\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{X}} \\ \dot{s} &\equiv \text{tr}(\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{X}} (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{X}} \\ \check{s} &\equiv \text{tr}(\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \Delta_n \tilde{\mathbf{X}}. \end{aligned}$$

Then

$$\begin{aligned} \mathbf{D}'\mathbf{D} &= \begin{pmatrix} \text{tr} \mathbf{I}_n & \text{tr} \mathbf{B}'\mathbf{B} \\ \text{tr} \mathbf{B}'\mathbf{B} & \text{tr}(\mathbf{B}'\mathbf{B})^2 \end{pmatrix} \\ &= \begin{pmatrix} n & n \\ n & \ddot{n} \end{pmatrix} \\ \mathbf{D}'(\mathbf{I}_n \otimes \mathbf{P})\mathbf{D} &= \begin{pmatrix} \text{tr} \mathbf{P} & \text{tr} \mathbf{B}'\mathbf{P}\mathbf{B} \\ \text{tr} \mathbf{B}'\mathbf{P}\mathbf{B} & \text{tr} \mathbf{B}'\mathbf{B}\mathbf{B}'\mathbf{P}\mathbf{B} \end{pmatrix} \\ &= \begin{pmatrix} k & s \\ s & \check{s} \end{pmatrix} \\ \mathbf{D}'(\mathbf{P} \otimes \mathbf{P})\mathbf{D} &= \begin{pmatrix} \text{tr} \mathbf{P} & \text{tr} \mathbf{B}'\mathbf{P}\mathbf{B} \\ \text{tr} \mathbf{B}'\mathbf{P}\mathbf{B} & \text{tr}(\mathbf{B}'\mathbf{P}\mathbf{B})^2 \end{pmatrix} \\ &= \begin{pmatrix} k & s \\ s & \dot{s} \end{pmatrix}. \end{aligned}$$

So

$$\begin{aligned}\boldsymbol{\Psi} &\equiv \mathbf{D}'(\mathbf{M} \otimes \mathbf{M})\mathbf{D} \\ &= \begin{pmatrix} n-k & n-s \\ n-s & \ddot{n} - 2\check{s} + \dot{s} \end{pmatrix}.\end{aligned}$$

So for the current case (2) becomes

$$\begin{aligned}\hat{\boldsymbol{\nu}} &= \mathbf{R}'[\mathbf{D}'(\mathbf{M} \otimes \mathbf{M})\mathbf{D}]^{-1}\mathbf{D}'(\hat{\boldsymbol{\varepsilon}} \otimes \hat{\boldsymbol{\varepsilon}}) \\ &= (\mathbf{X}'\mathbf{X} \otimes \mathbf{X}'\mathbf{X})^{-1}(\mathbf{X} \otimes \mathbf{X})'(\text{vec } \mathbf{I}_n, \text{vec } \mathbf{B}\mathbf{B}')\boldsymbol{\Psi}^{-1}(\text{vec } \mathbf{I}_n, \text{vec } \mathbf{B}\mathbf{B}')'(\hat{\boldsymbol{\varepsilon}} \otimes \hat{\boldsymbol{\varepsilon}}) \\ &= (\mathbf{X}'\mathbf{X} \otimes \mathbf{X}'\mathbf{X})^{-1}(\text{vec } \mathbf{X}'\mathbf{X}, \text{vec } \tilde{\mathbf{X}}'\tilde{\mathbf{X}})\boldsymbol{\Psi}^{-1}(\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}, \tilde{\boldsymbol{\varepsilon}}'\tilde{\boldsymbol{\varepsilon}})'\end{aligned}$$

Cluster-specific parameters

We now let σ^2 and τ^2 vary over clusters and the parameter vector becomes

$$\boldsymbol{\lambda} = (\sigma_1^2, \dots, \sigma_C^2, \tau_1^2, \dots, \tau_C^2)'$$

So now

$$\begin{aligned}\boldsymbol{\Sigma} &= \sum_c (\sigma_c^2 \mathbf{G}_c \mathbf{G}_c' + \tau_c^2 \mathbf{b}_c \mathbf{b}_c') \\ \mathbf{D} &= \sum_c (\mathbf{g}_c \mathbf{e}_c', \mathbf{h}_c \mathbf{e}_c'),\end{aligned}$$

with

$$\begin{aligned}\mathbf{g}_c &\equiv \text{vec} \mathbf{G}_c \mathbf{G}_c' \\ \mathbf{h}_c &\equiv \mathbf{b}_c \otimes \mathbf{b}_c,\end{aligned}$$

with properties

$$\begin{aligned}\mathbf{g}_c' \mathbf{g}_c &= n_c \\ \mathbf{h}_c' \mathbf{h}_c &= n_c^2 \\ \mathbf{g}_c' \mathbf{h}_c &= n_c,\end{aligned}$$

for $c = 1, \dots, C$, while $\mathbf{g}_c' \mathbf{g}_d = \mathbf{h}_c' \mathbf{h}_d = \mathbf{g}_c' \mathbf{h}_d = 0$ for $d \neq c$, and

$$\begin{aligned}(\mathbf{X} \otimes \mathbf{X})' \mathbf{g}_c &= \text{vec} \mathbf{X}'_c \mathbf{X}_c \\ (\mathbf{X} \otimes \mathbf{X})' \mathbf{h}_c &= \tilde{\mathbf{x}}_c \otimes \tilde{\mathbf{x}}_c \\ (\hat{\boldsymbol{\varepsilon}} \otimes \hat{\boldsymbol{\varepsilon}})' \mathbf{g}_c &= \hat{\boldsymbol{\varepsilon}}'_c \hat{\boldsymbol{\varepsilon}}_c \\ (\hat{\boldsymbol{\varepsilon}} \otimes \hat{\boldsymbol{\varepsilon}})' \mathbf{h}_c &= \tilde{\boldsymbol{\varepsilon}}_c^2,\end{aligned}$$

with ε_c the residuals of cluster c and $\bar{\varepsilon}_c$ their sum over the observations in the cluster, this all for $c = 1, \dots, C$. Further

$$\begin{aligned}
\mathbf{g}'_c(\mathbf{I}_n \otimes \mathbf{P})\mathbf{g}_c &= (\text{vec}\mathbf{G}_c\mathbf{G}'_c)' (\mathbf{I}_n \otimes \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') (\text{vec}\mathbf{G}_c\mathbf{G}'_c) \\
&= \text{tr}(\mathbf{G}_c\mathbf{G}'_c\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{G}_c\mathbf{G}'_c) \\
&= \text{tr}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_c\mathbf{X}_c \\
&\equiv s_c \\
\mathbf{h}'_c(\mathbf{I}_n \otimes \mathbf{P})\mathbf{h}_c &= (\mathbf{b}_c \otimes \mathbf{b}_c)' (\mathbf{I}_n \otimes \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') (\mathbf{b}_c \otimes \mathbf{b}_c) \\
&= n_c \tilde{\mathbf{x}}'_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{x}}_c \\
&\equiv n_c \tilde{s}_c \\
\mathbf{g}'_c(\mathbf{I}_n \otimes \mathbf{P})\mathbf{h}_c &= (\text{vec}\mathbf{G}_c\mathbf{G}'_c)' (\mathbf{I}_n \otimes \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') (\mathbf{b}_c \otimes \mathbf{b}_c) \\
&= \text{tr}(\mathbf{G}_c\mathbf{G}'_c\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{b}_c\mathbf{b}'_c) \\
&= \tilde{\mathbf{x}}'_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{x}}_c \\
&= \tilde{s}_c,
\end{aligned}$$

while it appears directly from the derivations that the terms across clusters are zero. This does not hold for the terms involving $\mathbf{P} \otimes \mathbf{P}$. There we have

$$\begin{aligned}
\mathbf{g}'_c(\mathbf{P} \otimes \mathbf{P})\mathbf{g}_d &= (\text{vec}\mathbf{G}_c\mathbf{G}'_c)' (\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' \otimes \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') (\text{vec}\mathbf{G}_d\mathbf{G}'_d) \\
&= \text{tr}(\mathbf{G}_c\mathbf{G}'_c\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{G}_d\mathbf{G}'_d\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') \\
&= \text{tr}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_c\mathbf{X}_c(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_d\mathbf{X}_d \\
&\equiv a_{cd} \\
\mathbf{h}'_c(\mathbf{P} \otimes \mathbf{P})\mathbf{h}_d &= (\mathbf{b}_c \otimes \mathbf{b}_c)' (\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' \otimes \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') (\mathbf{b}_d \otimes \mathbf{b}_d) \\
&= (\tilde{\mathbf{x}}'_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{x}}_d)^2 \\
&\equiv q_{cd} \\
\mathbf{g}'_c(\mathbf{P} \otimes \mathbf{P})\mathbf{h}_d &= (\text{vec}\mathbf{G}_c\mathbf{G}'_c)' (\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' \otimes \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') (\mathbf{b}_d \otimes \mathbf{b}_d) \\
&= \text{tr}(\mathbf{G}_c\mathbf{G}'_c\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{b}_d\mathbf{b}'_d\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') \\
&= \tilde{\mathbf{x}}'_d (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'_c\mathbf{X}_c(\mathbf{X}'\mathbf{X})^{-1}\tilde{\mathbf{x}}_d \\
&\equiv \ell_{cd}
\end{aligned}$$

We let Δ_s and $\Delta_{\tilde{s}}$ be the diagonal matrices containing the s_c and \tilde{s}_c and collect the a_{cd} , ℓ_{cd} and q_{cd} in the matrices \mathbf{A} , \mathbf{L} and \mathbf{Q} , respectively. Then we obtain

$$\begin{aligned}\mathbf{D}'\mathbf{D} &= \begin{pmatrix} \Delta_n & \Delta_n \\ \Delta_n & \Delta_n^2 \end{pmatrix} \\ \mathbf{D}'(\mathbf{I}_n \otimes \mathbf{P})\mathbf{D} &= \begin{pmatrix} \Delta_s & \Delta_{\tilde{s}} \\ \Delta_{\tilde{s}} & \Delta_n \Delta_{\tilde{s}} \end{pmatrix} \\ \mathbf{D}'(\mathbf{P} \otimes \mathbf{P})\mathbf{D} &= \begin{pmatrix} \mathbf{A} & \mathbf{L} \\ \mathbf{L}' & \mathbf{Q} \end{pmatrix}.\end{aligned}$$

So

$$\begin{aligned}\Phi &= \mathbf{D}'(\mathbf{M} \otimes \mathbf{M})\mathbf{D} \\ &= \begin{pmatrix} \Delta_n - 2\Delta_s + \mathbf{A} & \Delta_n - 2\Delta_{\tilde{s}} + \mathbf{L} \\ \Delta_n - 2\Delta_{\tilde{s}} + \mathbf{L}' & \Delta_n^2 - 2\Delta_n \Delta_{\tilde{s}} + \mathbf{Q} \end{pmatrix}.\end{aligned}$$

Combining the various elements, our unbiased estimator of the covariance matrix of the estimated regression coefficients is

$$\begin{aligned}\hat{\mathbf{v}} &= \mathbf{R}'[\mathbf{D}'(\mathbf{M} \otimes \mathbf{M})\mathbf{D}]^{-1}\mathbf{D}'(\hat{\boldsymbol{\epsilon}} \otimes \hat{\boldsymbol{\epsilon}}) \\ &= (\mathbf{X}'\mathbf{X} \otimes \mathbf{X}'\mathbf{X})^{-1}(\mathbf{X} \otimes \mathbf{X})' \sum_c (\mathbf{g}_c \mathbf{e}'_c, \mathbf{h}_c \mathbf{e}'_c) \Phi^{-1} \sum_c (\mathbf{g}_c \mathbf{e}'_c, \mathbf{h}_c \mathbf{e}'_c)' (\hat{\boldsymbol{\epsilon}} \otimes \hat{\boldsymbol{\epsilon}}) \\ &= (\mathbf{X}'\mathbf{X} \otimes \mathbf{X}'\mathbf{X})^{-1} \sum_c ((\text{vec} \mathbf{X}'_c \mathbf{X}_c) \mathbf{e}'_c, (\tilde{\mathbf{x}}_c \otimes \tilde{\mathbf{x}}_c) \mathbf{e}'_c) \Phi^{-1} \sum_c (\mathbf{e}_c \hat{\boldsymbol{\epsilon}}'_c \hat{\boldsymbol{\epsilon}}_c, \mathbf{e}_c \tilde{\boldsymbol{\epsilon}}_c^2)'\end{aligned}$$

Unrestricted error correlation within clusters

We now consider the case where the errors correlate freely within clusters, in a way that differs over clusters. The structure of Σ thus is

$$\begin{aligned}\Sigma &= \text{diag } \Lambda_c \\ &= \sum_c \mathbf{G}_c \Lambda_c \mathbf{G}'_c.\end{aligned}$$

This is a quite general structure, involving many parameters. It may even seem too generous in parameters but it has the merit to encompass all kinds of generalizations of the cluster-specific structure of Section 3.2 like factor structures. Since

$$\text{vec} \Sigma = \sum_c (\mathbf{G}_c \otimes \mathbf{G}_c) \text{vec} \Lambda_c,$$

the design matrix now is, using the $\dot{\otimes}$ notation introduced at the end of Section 2,

$$\begin{aligned}\mathbf{D} &= (\mathbf{G}_1 \otimes \mathbf{G}_1, \dots, \mathbf{G}_C \otimes \mathbf{G}_C) \\ &= \sum_c \mathbf{e}'_c \dot{\otimes} \mathbf{G}_c \otimes \mathbf{G}_c.\end{aligned}$$

Then, with

$$\mathbf{P}_c \equiv \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c,$$

we obtain

$$\begin{aligned}
\mathbf{D}'\mathbf{D} &= \sum_c \mathbf{e}_c \mathbf{e}'_c \dot{\otimes} \mathbf{I}_c \otimes \mathbf{I}_c \\
\mathbf{D}'(\mathbf{I}_n \otimes \mathbf{P})\mathbf{D} &= \left(\sum_c \mathbf{e}_c \dot{\otimes} \mathbf{G}'_c \otimes \mathbf{G}'_c \right) (\mathbf{I}_n \otimes \mathbf{P}) \left(\sum_c \mathbf{e}'_c \dot{\otimes} \mathbf{G}_c \otimes \mathbf{G}_c \right) \\
&= \sum_c \mathbf{e}_c \mathbf{e}'_c \dot{\otimes} \mathbf{I}_c \otimes \mathbf{P}_c \\
\mathbf{D}'(\mathbf{P} \otimes \mathbf{I}_n)\mathbf{D} &= \sum_c \mathbf{e}_c \mathbf{e}'_c \dot{\otimes} \mathbf{P}_c \otimes \mathbf{I}_c.
\end{aligned}$$

In the previous two cases we had a limited amount of parameters. But now we are faced with a possibly very large number of parameters, so we use (3) rather than (2).

Elaborating the expressions for \mathbf{A} and \mathbf{F} in (3) for the current case we get

$$\begin{aligned}
\mathbf{A} &= \mathbf{D}'\mathbf{D} - \mathbf{D}'(\mathbf{I}_n \otimes \mathbf{P})\mathbf{D} - \mathbf{D}'(\mathbf{P} \otimes \mathbf{I}_n)\mathbf{D} \\
&= \sum_c \mathbf{e}_c \mathbf{e}'_c \dot{\otimes} (\mathbf{I}_c \otimes \mathbf{I}_c - \mathbf{I}_c \otimes \mathbf{P}_c - \mathbf{P}_c \otimes \mathbf{I}_c) \\
&\equiv \sum_c \mathbf{e}_c \mathbf{e}'_c \dot{\otimes} \mathbf{A}_c \\
\mathbf{F} &= \mathbf{D}'(\mathbf{X} \otimes \mathbf{X}) \\
&= \sum_c \mathbf{e}_c \dot{\otimes} \mathbf{X}_c \otimes \mathbf{X}_c \\
&\equiv \sum_c \mathbf{e}_c \dot{\otimes} \mathbf{F}_c,
\end{aligned}$$

with \mathbf{A}_c and \mathbf{F}_c implicitly defined. Then

$$\begin{aligned}
\mathbf{F}'_c \mathbf{A}_c &= \mathbf{X}'_c \otimes \mathbf{X}'_c - \mathbf{X}'_c \otimes \mathbf{X}'_c \mathbf{X}_c (\mathbf{X}'_c \mathbf{X}_c)^{-1} \mathbf{X}'_c - \mathbf{X}'_c \mathbf{X}_c (\mathbf{X}'_c \mathbf{X}_c)^{-1} \mathbf{X}'_c \otimes \mathbf{X}'_c \\
&= \left(\mathbf{I}_{k^2} - \mathbf{I}_k \otimes \mathbf{X}'_c \mathbf{X}_c (\mathbf{X}'_c \mathbf{X}_c)^{-1} - \mathbf{X}'_c \mathbf{X}_c (\mathbf{X}'_c \mathbf{X}_c)^{-1} \otimes \mathbf{I}_k \right) \mathbf{F}'_c \\
&\equiv \mathbf{S}_c \mathbf{F}'_c,
\end{aligned}$$

with \mathbf{S}_c of order $k^2 \times k^2$ implicitly defined, so $\mathbf{F}'_c \mathbf{A}_c^{-1} = \mathbf{S}_c^{-1} \mathbf{F}'_c$ and

$$\begin{aligned}
\mathbf{F}' \mathbf{A}^{-1} \mathbf{F} &= \sum_c \mathbf{F}'_c \mathbf{A}_c^{-1} \mathbf{F}_c \\
&= \sum_c \mathbf{S}_c^{-1} (\mathbf{X}'_c \mathbf{X}_c \otimes \mathbf{X}'_c \mathbf{X}_c).
\end{aligned}$$

The final expression from (3) to be elaborated is

$$\begin{aligned}
\mathbf{F}' \mathbf{A}^{-1} \mathbf{D}'(\hat{\varepsilon} \otimes \hat{\varepsilon}) &= \left(\sum_c \mathbf{e}'_c \dot{\otimes} \mathbf{S}_c^{-1} \mathbf{F}'_c \right) \left(\sum_c \mathbf{e}_c \dot{\otimes} \mathbf{G}'_c \otimes \mathbf{G}'_c \right) (\hat{\varepsilon} \otimes \hat{\varepsilon}) \\
&= \sum_c \mathbf{S}_c^{-1} (\mathbf{X}'_c \hat{\varepsilon}_c \otimes \mathbf{X}'_c \hat{\varepsilon}_c).
\end{aligned}$$

Then (3) becomes

$$\hat{\mathbf{v}} = \left(\mathbf{X}' \mathbf{X} \otimes \mathbf{X}' \mathbf{X} + \sum_c \mathbf{S}_c^{-1} (\mathbf{X}'_c \mathbf{X}_c \otimes \mathbf{X}'_c \mathbf{X}_c) \right)^{-1} \sum_c \mathbf{S}_c^{-1} (\mathbf{X}'_c \hat{\varepsilon}_c \otimes \mathbf{X}'_c \hat{\varepsilon}_c).$$

Appendix B: Degrees of freedom with random effects

In this appendix we elaborate the denominator of (19) and derive estimators for the parameters in \hat{d}_ρ . We start with the former. First,

$$\text{trAM}\Sigma\text{MAM}\Sigma\text{M} = \sigma^4\text{trAMAM} + 2\sigma^2\tau^2\text{trB}'\text{MAMAMB} + \tau^4\text{tr(B}'\text{MAMB})^2. \quad (1)$$

The first term at the right-hand side was already elaborated in (18). As to the second term,

$$\text{AMA} = \sum_c \mathbf{G}_c \mathbf{A}_c^2 \mathbf{G}_c' - \sum_{c,d} \mathbf{G}_c \mathbf{A}_c \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_d \mathbf{A}_d \mathbf{G}_d'$$

so

$$\begin{aligned} \text{trB}'\text{MAMAMB} &= \text{tr} \sum_c \mathbf{A}_c^2 \mathbf{G}_c' \mathbf{M} \mathbf{B} \mathbf{B}' \mathbf{M} \mathbf{G}_c \\ &\quad - \text{tr} \sum_{c,d} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_d \mathbf{A}_d \mathbf{G}_d' \mathbf{M} \mathbf{B} \mathbf{B}' \mathbf{M} \mathbf{G}_c \mathbf{A}_c \mathbf{X}_c. \end{aligned}$$

From

$$\begin{aligned} \mathbf{G}'_c \mathbf{M} \mathbf{B} &= \mathbf{i}_c \mathbf{e}'_c - \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \\ &\equiv \mathbf{i}_c \mathbf{e}'_c - \mathbf{L}_c \end{aligned}$$

we obtain

$$\mathbf{G}'_c \mathbf{M} \mathbf{B} \mathbf{B}' \mathbf{M} \mathbf{G}_c = \mathbf{i}_c \mathbf{i}'_c - \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{x}}_c \mathbf{i}'_c - \mathbf{i}_c \tilde{\mathbf{x}}'_c (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c + \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{X}} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c$$

and, letting $\boldsymbol{\mu}_c \equiv (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c \mathbf{A}_c \mathbf{i}_c$, we have $\text{trB}'\text{MAMAMB} = T_1 + T_2$, with

$$\begin{aligned} T_1 &= \sum_c \mathbf{i}'_c \mathbf{A}_c^2 \mathbf{i}_c - 2 \sum_c \mathbf{i}'_c \mathbf{A}_c^2 \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{x}}_c + \text{tr} \sum_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{X}} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c \mathbf{A}_c^2 \mathbf{X}_c \\ T_2 &= \text{tr} \sum_{c,d} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_d \mathbf{A}_d (\mathbf{i}_d \mathbf{e}'_d - \mathbf{L}_d) (\mathbf{i}_c \mathbf{e}'_c - \mathbf{L}_c) \mathbf{e}_c \mathbf{A}_c \mathbf{X}_c \\ &= \sum_c \boldsymbol{\mu}'_c \mathbf{X}'_c \mathbf{X}_c \boldsymbol{\mu}_c - 2 \sum_c \tilde{\mathbf{x}}'_c (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c \mathbf{A}_c \mathbf{X}_c \boldsymbol{\mu}_c + \text{tr} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c \mathbf{A}_c \mathbf{X}_c (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}' \tilde{\mathbf{X}} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'_c \mathbf{A}_c \mathbf{X}_c. \end{aligned}$$

So far for the second term at the right-hand side of (27).

As to the third term, let $\lambda_c \equiv \mathbf{i}'_c \mathbf{A}_c \mathbf{i}_c$ and

$$\begin{aligned} \mathbf{B}'\mathbf{MAMB} &= \sum_c (\mathbf{B}' - \tilde{\mathbf{X}} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}') \mathbf{G}_c \mathbf{A}_c \mathbf{G}_c' (\mathbf{B} - \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1} \tilde{\mathbf{X}}') \\ &= \sum_c (\lambda_c \mathbf{e}_c \mathbf{e}'_c - \tilde{\mathbf{X}} \boldsymbol{\mu}_c \mathbf{e}'_c - \mathbf{e}_c \boldsymbol{\mu}'_c \tilde{\mathbf{X}}') + \tilde{\mathbf{X}} \mathbf{W} \tilde{\mathbf{X}}' \\ &\equiv \mathbf{S} + \tilde{\mathbf{X}} \mathbf{W} \tilde{\mathbf{X}}'. \end{aligned}$$

Then

$$\begin{aligned} \text{trS}^2 &= \sum_c (\lambda_c^2 - 4\mathbf{e}'_c \tilde{\mathbf{X}} \boldsymbol{\mu}_c + 2\boldsymbol{\mu}'_c \tilde{\mathbf{X}}' \tilde{\mathbf{X}} \boldsymbol{\mu}_c) + 2 \sum_{c,d} \tilde{\mathbf{x}}'_c \boldsymbol{\mu}_d \mathbf{e}'_d \tilde{\mathbf{x}}'_c \boldsymbol{\mu}_c \\ \text{trS}\tilde{\mathbf{X}}\mathbf{W}\tilde{\mathbf{X}}' &= \sum_c (\lambda_c \tilde{\mathbf{x}}'_c \mathbf{W} \tilde{\mathbf{x}}_c - 2\tilde{\mathbf{x}}'_c \mathbf{W} \tilde{\mathbf{X}} \boldsymbol{\mu}_c) \\ \text{tr}(\tilde{\mathbf{X}}\mathbf{W}\tilde{\mathbf{X}}')^2 &= \text{tr}(\mathbf{W}\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^2. \end{aligned}$$

Combining these elements we obtain an expression for $\text{tr}(\mathbf{B}'\mathbf{M}\mathbf{A}\mathbf{M}\mathbf{B})^2$.

In the spirit of the ‘‘unbiased’’ theme of this paper, we estimate d_ℓ in (15) by using unbiased estimators for $\sigma^4, \sigma^2\tau^2$ and τ^4 , which we will now derive. With the subscript to \mathbf{m}_{ab} denoting an expression with a \mathbf{M} s and b $\mathbf{B}\mathbf{B}'$ s, there holds

$$\begin{aligned} E(\hat{\varepsilon} * \hat{\varepsilon}) &= \mathbf{H}' E(\hat{\varepsilon} \otimes \hat{\varepsilon}) \\ &= \mathbf{H}'(\mathbf{M} \otimes \mathbf{M})\text{vec}(\sigma^2\mathbf{I}_n + \tau^2\mathbf{B}\mathbf{B}') \\ &= \sigma^2\mathbf{H}'\text{vec}\mathbf{M} + \tau^2\mathbf{H}'\text{vec}\mathbf{M}\mathbf{B}\mathbf{B}'\mathbf{M} \\ &\equiv \sigma^2\mathbf{m}_{10} + \tau^2\mathbf{m}_{21}. \end{aligned}$$

We additionally have

$$\begin{aligned} E(\hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon}) &= \mathbf{H}' E(\hat{\varepsilon} \otimes \mathbf{B}\mathbf{B}'\hat{\varepsilon}) \\ &= \mathbf{H}'(\mathbf{M} \otimes \mathbf{B}\mathbf{B}'\mathbf{M})\text{vec}(\sigma^2\mathbf{I}_n + \tau^2\mathbf{B}\mathbf{B}') \\ &= \sigma^2\mathbf{H}'\text{vec}\mathbf{B}\mathbf{B}'\mathbf{M} + \tau^2\mathbf{H}'\text{vec}\mathbf{B}\mathbf{B}'\mathbf{M}\mathbf{B}\mathbf{B}'\mathbf{M} \\ &\equiv \sigma^2\mathbf{m}_{11} + \tau^2\mathbf{m}_{22} \end{aligned}$$

and

$$\begin{aligned} E(\mathbf{B}\mathbf{B}'\hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon}) &= \mathbf{H}' E(\mathbf{B}\mathbf{B}'\hat{\varepsilon} \otimes \mathbf{B}\mathbf{B}'\hat{\varepsilon}) \\ &= \mathbf{H}'(\mathbf{B}\mathbf{B}'\mathbf{M} \otimes \mathbf{B}\mathbf{B}'\mathbf{M})\text{vec}(\sigma^2\mathbf{I}_n + \tau^2\mathbf{B}\mathbf{B}') \\ &= \sigma^2\mathbf{H}'\text{vec}\mathbf{B}\mathbf{B}'\mathbf{M}\mathbf{B}\mathbf{B}' + \tau^2\mathbf{H}'\text{vec}\mathbf{B}\mathbf{B}'\mathbf{M}\mathbf{B}\mathbf{B}'\mathbf{M}\mathbf{B}\mathbf{B}' \\ &\equiv \sigma^2\mathbf{m}_{12} + \tau^2\mathbf{m}_{23}. \end{aligned}$$

Then

$$\begin{aligned} \mathbf{i}'_n E(\hat{\varepsilon} * \hat{\varepsilon} * \hat{\varepsilon} * \hat{\varepsilon}) &= 3\mathbf{i}'_n \left((\sigma^2\mathbf{m}_{10} + \tau^2\mathbf{m}_{21}) * (\sigma^2\mathbf{m}_{10} + \tau^2\mathbf{m}_{21}) \right) \\ \mathbf{i}'_n E(\hat{\varepsilon} * \hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon}) &= \mathbf{i}'_n \left((\sigma^2\mathbf{m}_{10} + \tau^2\mathbf{m}_{21}) * (\sigma^2\mathbf{m}_{12} + \tau^2\mathbf{m}_{23}) \right. \\ &\quad \left. + 2(\sigma^2\mathbf{m}_{11} + \tau^2\mathbf{m}_{22}) * (\sigma^2\mathbf{m}_{11} + \tau^2\mathbf{m}_{22}) \right) \\ \mathbf{i}'_n E(\mathbf{B}\mathbf{B}'\hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon} * \mathbf{B}\mathbf{B}'\hat{\varepsilon}) &= 3\mathbf{i}'_n \left((\sigma^2\mathbf{m}_{12} + \tau^2\mathbf{m}_{23}) * (\sigma^2\mathbf{m}_{12} + \tau^2\mathbf{m}_{23}) \right). \end{aligned}$$

Solving the sample counterpart of this system readily leads to unbiased estimators for the three parameters,

$$\begin{pmatrix} 3\mathbf{i}'_n(\mathbf{m}_{10} * \mathbf{m}_{10}) & 6\mathbf{i}'_n(\mathbf{m}_{10} * \mathbf{m}_{21}) & 3\mathbf{i}'_n(\mathbf{m}_{21} * \mathbf{m}_{21}) \\ x & y & z \\ 3\mathbf{i}'_n(\mathbf{m}_{12} * \mathbf{m}_{12}) & 6\mathbf{i}'_n(\mathbf{m}_{12} * \mathbf{m}_{23}) & 3\mathbf{i}'_n(\mathbf{m}_{23} * \mathbf{m}_{23}) \end{pmatrix} \begin{pmatrix} \widehat{\sigma^4} \\ \widehat{\sigma^2\tau^2} \\ \widehat{\tau^4} \end{pmatrix} = \begin{pmatrix} \sum_i \hat{\varepsilon}_i^4 \\ \sum_i \hat{\varepsilon}_i^2 \hat{\varepsilon}_i^2 \\ \sum_i \hat{\varepsilon}_i^4 \end{pmatrix},$$

with

$$\begin{aligned} x &\equiv \mathbf{i}'_n(\mathbf{m}_{10} * \mathbf{m}_{12} + 2\mathbf{m}_{11} * \mathbf{m}_{11}) \\ y &\equiv \mathbf{i}'_n(\mathbf{m}_{10} * \mathbf{m}_{23} + \mathbf{m}_{21} * \mathbf{m}_{12} + 4\mathbf{m}_{22} * \mathbf{m}_{11}) \\ z &\equiv \mathbf{i}'_n(\mathbf{m}_{21} * \mathbf{m}_{23} + 2\mathbf{m}_{22} * \mathbf{m}_{22}). \end{aligned}$$

Efficient computation can be based on $\mathbf{H}'\text{vec}\mathbf{R}\mathbf{S}' = (\mathbf{R} * \mathbf{S})\mathbf{i}_\ell$ for \mathbf{R} and \mathbf{S} of order $n \times \ell$.

Appendix C: Consistency in a simple setting

The simulations highlight that UV1 can offer a size correct test even with only a single treated cluster, while UV2 and UV3 require a somewhat larger number of treated clusters. In this section, we explore these findings from a theoretical perspective. We derive the conditions under which the three variance estimators are consistent in a simple model that is rich enough to explain the observed features from our simulations. We consider a setting with a single regressor, which is a treatment dummy that is equal to one in t_c out of C clusters. The design is balanced, so that each cluster contains n/C observations. With the definitions given in the paper, we then find

$$\mathbf{X}'\mathbf{X} = (n \cdot t_c)/C, \quad \tilde{\mathbf{X}}'\tilde{\mathbf{X}} = (n^2 \cdot t_c)/C^2. \quad (2)$$

We assume that the regression errors $\varepsilon \sim N(\mathbf{0}, \Sigma)$. We take Σ as in Section 3.1, so that all variance estimators are unbiased. Without changing the proof, we can take Σ as in Section 3.2 and show consistency of UV2 and UV3. The relevant property of Σ is that its maximum eigenvalue satisfies $\lambda_{\max}(\Sigma) \leq M \cdot n/C$. This condition holds in the specifications of Section 3.1 and Section 3.2. In this section M denotes a generic positive constant that can differ between appearances.

A sufficient condition for $\hat{v}/v \rightarrow_p 1$ is that $\text{var}(\hat{v})/v^2 \rightarrow 0$. Note that this implies that the degrees of freedom, defined as $2v^2/\text{var}(\hat{v})$, diverge. Using the expressions derived in Section 4, we have

$$\begin{aligned} \text{var}(\hat{v})/v^2 &= 2\text{tr}(\mathbf{A}\mathbf{M}\Sigma\mathbf{M}\mathbf{A}\mathbf{M}\Sigma\mathbf{M})/v^2 \\ &\leq M \cdot \lambda_{\max}(\Sigma)^2 (\mathbf{X}'\mathbf{X})^2 \text{tr}(\mathbf{A}^2) \\ &\leq M \cdot (n/C)^4 t_c^2 \text{tr}(\mathbf{A}^2), \end{aligned} \quad (3)$$

where \mathbf{A} is the block diagonal matrix with blocks \mathbf{A}_c as given in Section 4 in the paper. We now proceed to derive explicit expressions for $\text{tr}(\mathbf{A}^2)$ for the variance estimators UV1-UV3.

UV1 From Section 4, we have that

$$\mathbf{A}_c = r_1 \mathbf{I}_c + r_2 \mathbf{i}_c \mathbf{i}_c', \quad (r_1, r_2) = \mathbf{f}'_c (\mathbf{X}'\mathbf{X} \otimes \mathbf{X}'\mathbf{X})^{-1} (\text{vec} \mathbf{X}'\mathbf{X}, \text{vec} \tilde{\mathbf{X}}'\tilde{\mathbf{X}}) \Psi^{-1} \quad (4)$$

The matrix Ψ defined in Section 3.1 depends on the following quantities,

$$\ddot{n} = \sum_c (n/C)^2 = n^2/C, \quad s = n/C, \quad \dot{s} = (n/C)^2, \quad \check{s} = (n/C)^2.$$

Since $\mathbf{s}\Psi$ is a 2×2 matrix, its inverse is easily obtained as

$$\begin{aligned} \Psi^{-1} &= \frac{1}{n} \begin{pmatrix} 1 - n^{-1} & 1 - C^{-1} \\ 1 - C^{-1} & (n/C)(1 - C^{-1}) \end{pmatrix} \\ &= \frac{1}{n} \frac{1}{(n/C - 1)(1 - C^{-1})} \begin{pmatrix} (n/C)(1 - C^{-1}) & -(1 - C^{-1}) \\ -(1 - C^{-1}) & 1 - n^{-1} \end{pmatrix}. \end{aligned}$$

Then, using (2),

$$(\text{vec} \mathbf{X}'\mathbf{X}, \text{vec} \tilde{\mathbf{X}}'\tilde{\mathbf{X}}) \Psi^{-1} = \frac{1}{C} \frac{1}{(n/C - 1)(1 - C^{-1})} (0, t_c(n/C - 1)) = (0, t_c/(C - 1)).$$

Using (4), we find that $r_1 = 0$ and $r_2 = C^2/(n^2 \cdot (C - 1) \cdot t_c)$. Hence,

$$\text{tr}(\mathbf{A}^2) = \sum_c \text{tr}(\mathbf{A}_c^2) = C \cdot r_2^2 \cdot (n/C)^2 = \frac{C^2}{t_c^2 n^2} \frac{C}{(C-1)^2}.$$

Substituting this into (3), we find that

$$\text{var}(\hat{v})/v^2 \leq M \cdot \left(\frac{n}{C}\right)^2 \frac{C}{(C-1)^2}.$$

We conclude that for UV1 to be consistent, we require that the number of clusters grows sufficiently fast to guarantee that $n^2/C^3 \rightarrow 0$. Importantly, consistency only depends on the number of clusters, and not on the number of treated clusters t_c .

UV2 Assume that the number of treated clusters $t_c > 2$. From Section 4, we have

$$\mathbf{A}_c = r_{1c} \mathbf{I}_c + r_{2c} \mathbf{i}_c \mathbf{i}_c', \quad (\mathbf{r}'_1, \mathbf{r}'_2) = \mathbf{f}'_\ell(\mathbf{X}'\mathbf{X} \otimes \mathbf{X}'\mathbf{X})^{-1} \sum_c \left((\text{vec} \mathbf{X}'_c \mathbf{X}_c) \mathbf{e}'_c, (\tilde{\mathbf{x}}_c \otimes \tilde{\mathbf{x}}_c) \mathbf{e}'_c \right) \mathbf{\Phi}^{-1}. \quad (5)$$

Note that in the definition of $\mathbf{\Phi}$ given in Section 3.2 the elements $a_{cd}, \ell_{cd}, q_{cd}$ equal zero when one of the clusters is untreated. As a result, we have

$$\mathbf{\Phi} = \begin{pmatrix} \left(\frac{n}{C} - \frac{2}{t_c} \right) \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} & \mathbf{0} & \frac{n}{C} \left[\frac{t_c-2}{t_c} \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} \right] & \mathbf{0} \\ \mathbf{0} & \frac{n}{C} \mathbf{I}_{C-t_c} & \mathbf{0} & \frac{n}{C} \mathbf{I}_{C-t_c} \\ \frac{n}{C} \left[\frac{t_c-2}{t_c} \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} \right] & \mathbf{0} & \left(\frac{n}{C} \right)^2 \left[\frac{t_c-2}{t_c} \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} \right] & \mathbf{0} \\ \mathbf{0} & \frac{n}{C} \mathbf{I}_{C-t_c} & \mathbf{0} & \left(\frac{n}{C} \right)^2 \mathbf{I}_{C-t_c} \end{pmatrix}.$$

We can analytically invert this matrix by rearranging it into a block diagonal matrix and first invert the diagonal blocks that are formed by

$$\mathbf{B}_1 = \begin{pmatrix} 1 & 0 \\ 0 & \frac{n}{C} \end{pmatrix} \begin{pmatrix} \left(\frac{n}{C} - \frac{2}{t_c} \right) \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} & \frac{t_c-2}{t_c} \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} \\ \frac{t_c-2}{t_c} \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} & \frac{t_c-2}{t_c} \mathbf{I}_{t_c} + \frac{1}{t_c^2} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & \frac{n}{C} \end{pmatrix}.$$

and

$$\mathbf{B}_2 = \begin{pmatrix} \frac{n}{C} \mathbf{I}_{C-t_c} & \frac{n}{C} \mathbf{I}_{C-t_c} \\ \frac{n}{C} \mathbf{I}_{C-t_c} & \left(\frac{n}{C} \right)^2 \mathbf{I}_{C-t_c} \end{pmatrix}.$$

The inverse of the first diagonal block is simplified by that fact that the upper right, lower left and lower right blocks are identical. We obtain

$$\mathbf{B}_1^{-1} = \begin{pmatrix} 1 & 0 \\ 0 & \frac{n}{C} \end{pmatrix} \begin{pmatrix} \left(\frac{n}{C} - 1 \right)^{-1} \mathbf{I}_{t_c} & -\left(\frac{n}{C} - 1 \right)^{-1} \mathbf{I}_{t_c} \\ -\left(\frac{n}{C} - 1 \right)^{-1} \mathbf{I}_{t_c} & \left(\left(\frac{n}{C} - 1 \right)^{-1} + \frac{t_c}{t_c-2} \right) \mathbf{I}_{t_c} - \frac{1}{(t_c-2)(t_c-1)} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & \frac{n}{C} \end{pmatrix},$$

The inverse of the second block is

$$\mathbf{B}_2^{-1} = \begin{pmatrix} \frac{n}{C} \mathbf{I}_{C-t_c} & \frac{n}{C} \mathbf{I}_{C-t_c} \\ \frac{n}{C} \mathbf{I}_{C-t_c} & \left(\frac{n}{C} \right)^2 \mathbf{I}_{C-t_c} \end{pmatrix}^{-1} = \frac{1}{\frac{n}{C} - 1} \begin{pmatrix} \mathbf{I}_{C-t_c} & -\frac{C}{n} \mathbf{I}_{C-t_c} \\ -\frac{C}{n} \mathbf{I}_{C-t_c} & \frac{C}{n} \mathbf{I}_{C-t_c} \end{pmatrix}$$

Rearranging back into the original form of Φ , we obtain

$$\Phi^{-1} = \left(\frac{n}{C} - 1\right)^{-1} \begin{pmatrix} \mathbf{I}_{t_c} & \mathbf{0} & -\frac{c}{n}\mathbf{I}_{t_c} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{C-t_c} & \mathbf{0} & -\frac{c}{n}\mathbf{I}_{C-t_c} \\ -\frac{c}{n}\mathbf{I}_{t_c} & \mathbf{0} & \left(\frac{n}{C} - 1\right)\left(\frac{c}{n}\right)^2 \left[\left(\frac{n}{C} - 1\right)^{-1} + \frac{t_c}{t_c-2} \right] \mathbf{I}_{t_c} - \frac{1}{(t_c-2)(t_c-1)} \mathbf{i}_{t_c} \mathbf{i}'_{t_c} & \mathbf{0} \\ \mathbf{0} & -\frac{c}{n}\mathbf{I}_{C-t_c} & \mathbf{0} & \frac{c}{n}\mathbf{I}_{C-t_c} \end{pmatrix}.$$

Using that for the treated clusters $\mathbf{X}'_c \mathbf{X}_c = n/C$ and $\tilde{\mathbf{x}}_c \otimes \tilde{\mathbf{x}}_c = (n/C)^2$, we get that

$$\begin{aligned} \sum_c \left((\text{vec} \mathbf{X}'_c \mathbf{X}_c) \mathbf{e}'_c, (\tilde{\mathbf{x}}_c \otimes \tilde{\mathbf{x}}_c) \mathbf{e}'_c \right) \Phi^{-1} &= \left(\mathbf{0}'_c, \left(\frac{t_c}{t_c-2} - \frac{t_c}{(t_c-2)(t_c-1)} \right) \mathbf{i}'_{t_c}, \mathbf{0}'_{C-t_c} \right) \\ &= \left(\mathbf{0}'_c, \frac{t_c}{t_c-1} \mathbf{i}'_{t_c}, \mathbf{0}'_{C-t_c} \right). \end{aligned}$$

In (5) we now have $\mathbf{r}_1 = \mathbf{0}$ and $\mathbf{r}_{2c} = \frac{1}{t_c^2} \left(\frac{c}{n}\right)^2 \frac{t_c}{t_c-1}$ if cluster c is treated and zero otherwise. Then,

$$\text{tr}(\mathbf{A}^2) = t_c \left(\frac{n}{C}\right)^2 \cdot \frac{1}{t_c^4} \left(\frac{C}{n}\right)^4 \frac{t_c^2}{(t_c-1)^2}.$$

Substituting this into (3) we conclude that

$$\text{var}(\hat{v})/v^2 \leq M \cdot \left(\frac{n}{C}\right)^2 \frac{t_c}{(t_c-1)^2}.$$

We conclude that UV2 is consistent for v when $n^2/(C^2 \cdot t_c) \rightarrow 0$. A necessary condition for this to happen is that the number of treated clusters $t_c \rightarrow \infty$. This stands in marked contrast with the finding for UV1 above.

UV3 Assume that $t_c > 2$.

$$\mathbf{A}_c = \mathbf{X}_c \mathbf{Q}_c \mathbf{X}'_c, \quad (\text{vec} \mathbf{Q}_c)' = \mathbf{f}'_c \left(\mathbf{X}'_c \mathbf{X}_c \otimes \mathbf{X}'_c \mathbf{X}_c + \sum_c \mathbf{S}_c^{-1} (\mathbf{X}'_c \mathbf{X}_c \otimes \mathbf{X}'_c \mathbf{X}_c) \right)^{-1} \mathbf{S}_c^{-1}. \quad (6)$$

If cluster c is treated, we have $S_c = 1 - 2/t_c$, while if cluster c is not treated, we have $S_c = 1$. Then,

$$\mathbf{X}'_c \mathbf{X}_c \otimes \mathbf{X}'_c \mathbf{X}_c + \sum_c \mathbf{S}_c^{-1} (\mathbf{X}'_c \mathbf{X}_c \otimes \mathbf{X}'_c \mathbf{X}_c) = (n \cdot t_c)^2 / C^2 + t_c^2 / (t_c - 2)(n/C)^2 = \left(\frac{nt_c}{C}\right)^2 \cdot \frac{t_c-1}{t_c-2}.$$

Then with A_c from (6), we find

$$\text{tr}(\mathbf{A}^2) = \sum_c \text{tr}(\mathbf{A}_c^2) = t_c \cdot \frac{n^2}{C^2} \frac{C^4}{n^4 \cdot t_c^4} \frac{(t_c-2)^2}{(t_c-1)^2} \frac{t_c^2}{(t_c-2)^2} = \frac{C^2}{n^2 t_c (t_c-1)^2}.$$

Substituting this into (3), we conclude that

$$\text{var}(\hat{v})/v^2 \leq M \cdot \left(\frac{n}{C}\right)^2 \frac{t_c}{(t_c-1)^2}.$$

For consistency of UV3 we therefore require that $n^2/(C^2 \cdot t_c) \rightarrow 0$. This is the same condition as for UV2, so that again we require the number of treated clusters $t_c \rightarrow \infty$.